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ACCURACY OF REMOTELY SENSED DATA: SAMPLING AND ANALYSIS PROCEDURES

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Remote Sensing Research Report 82-1

Accuracy of Remotely Sensed Data: Sampling and Analysis Procedures

by

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16. Abstract

The main body of this report is divided into two parts. The first part presents a review and update of the discrete multivariate analysis techniques used for accuracy assessment. Appendix A contains a listing of the computer program written to implement these techniques. The second part presents new work on evaluating accuracy assessment using Monte Carlo simulation with different sampling schemes.

Appendix B contains the results of the accuracy assessment analysis for the eight error matrices from the mapping effort of the San Juan National Forest. Appendix C contains a method of estimating the sample size requirements for implementing the accuracy assessment procedures. Appendix D contains a proposed method for determining the reliability of change detection between two maps of the same area produced at different times.

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PREFACE

The authors would like to thank the Applications Branch of the EROS Data Center for their help in the sampling simulation section of this report. Special thanks go to Tom Loveland and Wayne Miller for supplying the data and also to John Szajgin and Jeff Newcomer for their guidance and encouragement.

Acknowledgment should also go to Robert B. Mattson, James A. Shafer, and Bruce F. Short for their work on the photo interpretation used in the accuracy assessment of the R2MAP classification for the San Juan National Forest. Thanks also to all those who helped code all the data and prepare it for analysis.

ABSTRACT

The main body of this report is divided into two parts. The first part presents a review and update of the discrete multivariate analysis techniques used for accuracy assessment. Appendix A contains a listing of the computer program written to implement these techniques. The second part presents new work on evaluating accuracy assessment using Monte Carlo simulation with different sampling schemes.

Appendix B contains the results of the accuracy assessment analysis for the eight error matrices from the mapping effort of the San Juan National Forest. Appendix C contains a method of estimating the sample size requirements for implementing the accuracy assessment procedures. Appendix D contains a proposed method for determining the reliability of change detection between two maps of the same area produced at different times.

1.0 Introduction

This report is divided into two parts. The first part deals with a short review and update of material described in last year's report (Congalton *et al*. 1981). This work involves assessing the accuracy of remotely sensed data using discrete multivariate analysis statistical techniques.

The second part of this report describes the work currently in progress on sampling for accuracy assessment. This research is investigating different sampling schemes using Monte Carlo simulation techniques. Although this work is not complete, some valuable results have already been achieved.

2.0 Discrete Multivariate Analysis Techniques for Accuracy Assessment

The three analysis procedures reviewed here all involve error matrices. An error matrix is a square array of numbers set out in rows and columns which express the number of cells assigned as a particular land cover type relative to the actual cover type as verified in the field. The columns usually represent the reference data and the rows indicate either the Landsat classification or the photo interpretation. The discrete multivariate analysis procedures are performed on the error matrices.

2.1 Review of the Normalization Procedure

The first comparison procedure (Bishop et al. 1975) allows individual cell values in each error matrix to be compared. This comparison is made possible by a process called normalizing the error matrix. This normalization process is a way of standardizing each matrix so that a direct comparison of individual cell values is possible. This procedure always converges to a unique set of maximum likelihood estimates and as such is the best algorithm to use in this case (Fienberg 1970). An assumption made by this process is that all cells are of equal importance.

Normalization of an error matrix is an iterative process by which the rows and columns of the matrix are successively balanced until each row and column adds up to a given value (marginal). This process causes each cell value to be influenced by all the other cell values in its corresponding row and column. Each cell value is then a combination of reference data and remote sensor data and is representative of both commission and omission errors for that land cover category. Because each row and column must add to a given marginal, the cell values in corresponding positions of two or more error matrices can then be compared without regard for differences in sample size between matrices.

The normalization process is performed by a computer program called MARGFIT (Congalton et al. 1981). For additional details and examples of this process see Congalton (1981).

2.2 Update of the Test of Agreement Procedure

The second method of comparison is a procedure that tests for agreement between two or more error matrices (Bishop et al. 1975). This measure of agreement is based on the difference between the actual agreement of the classification (i.e., agreement between remote sensor data and reference data indicated by the major diagonal) and the chance agreement which is indicated by the row and column marginals. This measure of agreement called KHAT is calculated by:

$$\hat{k} = \frac{\sum_{i=1}^{n} x_{ii} - \sum_{i=1}^{n} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{n} (x_{i+} * x_{+i})}$$

where:

n is the number of rows in the matrix

x_{ii} is the number of observations in row i and column i

x_{i+} and x_{+i} is the marginal total of row i and column i respectively

and N is the total number of observations.

A KHAT value is calculated for each matrix and is a measure of how well the Landsat classification or photo interpretation agrees with the reference data. The approximate large sample variance of KHAT as determined by the delta method is:

$$\hat{\sigma}(\hat{k}) = \frac{1}{N} \quad \frac{\theta_1(1 - \theta_1)}{(1 - \theta_2)^2} + \frac{2(1 - \theta_1)(2\theta_1 \theta_2 - \theta_3)}{(1 - \theta_2)^3} + \frac{(1 - \theta_1)^2(\theta_4 - 4\theta_2^2)}{(1 - \theta_2)^4}$$

where:

$$\theta_1 = \sum_{i=1}^{n} \frac{x_{ii}}{N} \qquad \theta_3 = \sum_{i=1}^{n} \frac{x_{ii}}{N} \left(\frac{x_{i+}}{N} + \frac{x_{+i}}{N} \right)$$

$$\theta_2 = \sum_{i=1}^{n} \frac{x_{i+} * x_{+i}}{N^2} \qquad \theta_4 = \sum_{\substack{i=1 \\ j=1}}^{n} \frac{x_{ij}}{N} \left(\frac{x_{+j}}{N} + \frac{x_{i+}}{N} \right)^2$$

Confidence intervals can be calculated for KHAT using this approximate large sample variance of KHAT. These confidence intervals were used previously as a method for testing the significant difference between two error matrices. However, exact hypothesis tests are now available and should be used instead of the confidence intervals.

A test for significance of KHAT can be performed to determine if the agreement between the Landsat classification or photo interpretation and reference data is significantly greater than zero. Also a test for the significant difference between two independent KHAT's can be performed by evaluating the normal curve deviate (Cohen 1960). The test statistic for significant difference is approximately:

$$\frac{\hat{k}_1 - \hat{k}_2}{\sqrt{\hat{\sigma}_1^2 + \hat{\sigma}_2^2}} \sim Z$$

The FORTRAN computer program used to calculate this measure of agreement, KHAT, is called KAPPA. This program has been updated to

include the exact hypothesis tests described above (Appendix A). Given the original matrix, the computer program implements a procedure that calculates the KHAT value and its corresponding variance. A confidence interval around KHAT is also computed along with the test statistic for significance of KHAT. All these values plus the values used in calculating the variance (i.e, TH1, TH2, TH3, and TH4) are printed out along with the original error matrix. The algorithm then computes the test statistic for significant difference between independent KHAT's for each possible pair of matrices. These values are printed out in a summary table at the end of the program.

2.3 Update of KAPPA Example

As already mentioned, an actual test statistic is now available to test for significant differences between error matrices. In last year's report (Congalton et al. 1981) examples were given in which only the confidence intervals were compared. Presented below is an updated analysis of the results that appeared last year in Table 6, page 19. This data compares four classification algorithms provided by Hoffer (1975).

Table 1. Table of updated KHAT values.

MATRIX	KHAT	VARIANCE	COMPARISON	Z STATISTIC	Result	
					95%	90%
Nonsupervised (10 cluster) NS-10	0.60479	.00073735	NS-10, NS-20	0.47475	NS	NS
Nonsupervised (20 cluster) NS-20	0.58573	.00087456	NS-10, MS	3.00930	S	S
			NS-10, MC	-2.93550	S	S
Modifed Supervised MS	0.47581	.00109972	NS-20, MS	2.47390	S	S
			NS-20, MC	-3.28090	S	S
Modified Clustering MC	0.71846	.00076218	MS, MC	-5.62360	S	S

This analysis shows that there is not a significant difference between the classification obtained using a nonsupervised approach with 20 clusters and that obtained using a nonsupervised approach with 10 clusters. However, the results of all the other tests yield significant differences between classification algorithms.

2.4 Review of the Multi-factor Comparison Procedure

The multi-factor comparison procedure allows more than one factor affecting the classification accuracy to be examined at the same time. The log-linear approach as described by Fienberg (1980) and Bishop et al. (1975) is a method by which many variables and the interaction between these variables can be tested simultaneously to see which are necessary (i.e., significant) for explaining the classification accuracy.

The simplest model (combination of variables) that provides a good fit to the data is chosen using a model selection procedure. This procedure allows the user to systematically search all possible models and choose the simplest model that provides a good fit to the data. First all uniform order models are tested (i.e., models with all possible n-way interactions, where n ranges from 1 to the number of factors) and the simplest good fit model is chosen. Each interaction of the chosen model is then tested for significance. If the interaction is not significant it is dropped until a model is found in which all the factors and

interactions of factors are significant. For a more detailed description of this stepwise model selection procedure, see Fienberg (1980) Section 5.3. The criteria for selecting a good model is based on a Likelihood Ratio, G^2, and the degrees of freedom for the model. The Likelihood Ratio has an asymptotically chi-square distribution and therefore the critical value for testing if the model is a good fit can be obtained from a chi-square table using the appropriate degrees of freedom.

The Likelihood Ratio is calculated using an Iterative Proportional Fitting procedure (Fienberg 1980 and Bishop et al. 1975). This procedure uses a method of successive approximations to converge to the maximum likelihood estimates of the minimum sufficient statistics as defined by the model. Therefore, the log-linear approach allows for analysis of multi-way tables with many factors. For example, error matrices generated using different dates, different algorithms, and different analysts all of the same scene of imagery can be put together and the factors necessary to explain the classification accuracy analyzed. This example would yield a five-way table with the five factors being: date, algorithm, analyst, Landsat classification, and reference data. Testing this five-way table would determine the simplest model of factors and interactions that best explain the results.

2.5 Multi-factor Comparison Example

The data used to test the combined effects of different classification algorithms and enhancement techniques on Landsat classification accuracy was supplied by Gregg et al. (1979). In this example two classification algorithms are performed on smoothed and unsmoothed imagery and the combined effects are studied. The factors and effects for this four-way table are listed in Table 2 and the original matrices presented in Table 3. Each algorithm classified the data into one of ten land cover categories (Table 4).

A model selection procedure was performed on the four-way table beginning with the uniform order models (Table 5). The results of this procedure yields the simples best fit model to the data (Table 6). This model, [14] [24] [34], indicates that no three or four-way interactions are needed to explain the data. Instead, there are only two-way interactions involved. In other words, there is a combined effect due to each explanatory variable (i.e., algorithm, enhancement, and reference data) separately with the response variable. However, there are no higher order interactions. Therefore, each effect is important and no factor can be eliminated. The assumption that the error matrices adequately represent the actual classification must hold here if any of these results are to be meaningful.

TABLE 2

A list of factors for the four-way table comparing enhancement and classification algorithms.

FACTOR	EFFECT	
I (1)	Classification Algorithm	1=maximum likelihood 2=cononical domain
J (2)	Resampling Technique	1=smoothed 2=unsmoothed
K (3)	Reference Data	1-10 (See Table 4)
L (4)	Landsat Data	1-10 (See Table 4)

TABLE 3

The original four-way table for comparing enhancement techniques and classification algorithms.

I=1 J=1

reference data (K)

landsat data (L)	1	2	3	4	5	6	7	8	9	10
1	69	128	0	20	4	0	2	4	9	0
2	17	60	0	9	0	0	0	7	15	2
3	10	38	2	14	1	3	2	5	13	1
4	16	57	8	165	31	4	4	7	17	5
5	0	5	6	38	33	17	12	7	8	17
6	17	19	0	8	2	0	1	16	76	3
7	2	0	1	1	9	7	27	9	3	5
8	8	23	4	22	8	14	10	164	178	5
9	5	6	1	11	7	3	5	113	569	1
10	0	0	8	6	4	4	3	0	0	15

*See Table 4 for a list of the land cover categories.

TABLE 3

(continued)

I=1 J=2

reference data (K)

landsat data (L)	1	2	3	4	5	6	7	8	9	10
1	87	166	0	29	6	1	3	6	20	0
2	16	53	0	10	1	1	0	6	13	1
3	5	23	1	13	1	0	0	2	6	1
4	12	49	8	167	26	2	4	7	18	2
5	1	3	6	29	39	15	8	10	9	21
6	7	11	0	8	1	1	1	9	45	2
7	3	0	3	0	6	7	33	8	1	11
8	5	22	2	21	8	19	12	174	159	4
9	11	9	3	12	8	3	2	110	617	1
10	3	0	7	3	3	3	3	0	3	11

*See Table 4 for a list of the land cover categories.

TABLE 3

(continued)

I=2 J=1

reference data (K)

Landsat data (L)	1	2	3	4	5	6	7	8	9	10
1	59	112	0	23	3	0	1	4	9	0
2	22	53	0	10	1	0	0	6	16	1
3	14	60	1	23	1	3	2	7	13	1
4	15	55	8	189	35	4	4	6	12	3
5	1	3	8	28	30	15	12	3	5	19
6	11	15	1	5	2	1	0	9	47	3
7	2	0	1	1	8	6	28	9	3	7
8	7	27	4	24	11	17	11	156	157	6
9	16	11	1	13	6	3	6	132	626	4
10	0	0	6	2	2	3	2	0	0	10

*See Table 4 for a list of the land cover categories.

TABLE 3

(continued)

I=2 J=2

Landsat data (L)	reference data (K) 1	2	3	4	5	6	7	8	9	10
1	70	141	0	28	4	1	2	6	19	0
2	26	53	0	6	1	1	0	4	10	0
3	11	48	0	25	3	0	0	4	8	1
4	12	53	6	167	34	1	4	6	17	2
5	0	1	10	25	33	15	6	8	8	22
6	1	5	1	5	1	1	0	4	18	0
7	2	0	3	0	5	8	34	8	0	14
8	4	20	2	13	9	21	14	164	127	5
9	21	15	3	17	8	3	3	128	681	2
10	0	0	5	1	1	1	3	0	0	8

*See Table 4 for a list of the land cover categories.

TABLE 4

A list of the land cover categories for the four-way table comparing enhancement and classification methods.

CATEGORY NUMBER	LAND COVER TYPE
#1	disturbed/recent clearcut
#2	planted clearcut
#3	mixed reproduction (hardwood/conifer)
#4	young reproduction (conifer)
#5	old reproduction (conifer)
#6	mixed pole/saw timber (hardwood/conifer)
#7	conifer - pole timber
#8	conifer - saw timber
#9	old growth
#10	hardwood

TABLE 5

The uniform order models for the four-way table comparing enhancement techniques and classification algorithms.

MODEL	G^2	df	RESULT
[1][2][3][4]	10888.87281	352	poor fit
A [12][13][14][23][24][34]	145.86428	234	good fit
[123][124][134][234]	20.90917	54	good fit

TABLE 6

The model selection process for the four-way table comparing enhancement techniques and classification algorithms.

MODEL	G^2	df	RESULT
[12][13][14][23][24]	10732.65712	315	poor fit
[12][13][14][23][34]	230.22104	243	good fit
[12][13][14][24][34] B	147.83246	243	good fit
[12][13][23][24][34]	227.51772	243	good fit
[12][14][23][24][34]	156.53131	243	good fit
[13][14][23][24][34]	146.04061	235	good fit

model B best and good fit

$G^2(B) - G^2(A) = 2.06819 \sim \chi'_{9df}$ not significant so drop [23]

TABLE 6

(continued)

MODEL	G^2	df	RESULT
[12][13][14][24]	10733.8278	324	poor fit
[12][13][14][34]	231.3918	252	good fit
[12][13][24][34]	229.4802	252	good fit
[12][14][24][34]	158.4941	252	good fit
[13][14][24][34] C	148.0034	252	good fit

model C best and good fit

$G^2(C) - G^2(B) = 0.1709195 \sim \chi^2_{1df}$ not significant so drop[12]

TABLE 6

(continued)

MODEL	G^2	df	RESULT
[13][14][24]	10733.99876	325	poor fit
[13][14][34][2]	231.43485	253	good fit
[13][24][34]	229.52108	253	good fit
[14][24][34] D	158.66500	253	good fit

model D best and good fit

$G^2(D) - G^2(C) = 10.66162 \sim \chi^2_{1df}$ not significant so drop [13]

TABLE 6

(continued)

MODEL	G^2	df	RESULT
[14][24][3]	10734.29202	334	poor fit
[14][34][2]	242.09646	262	good fit
[24][34][1] E	229.81433	262	good fit
model E best and good fit choose D $G^2(E) - G^2(D) = 71.14933 \sim \chi^2_{9df}$ significant so can't drop [14]			

3.0 Sampling Simulation for Accuracy Assessment

This research involved a sampling simulation study using three different vegetation environments of varying spatial complexity. These three environments were forest, range, and agricultural lands. Small areas (approximately 200 x 200 pixels) called subscenes were chosen from each of the three environments. Some of these subscenes contained large homogeneous areas of vegetation while others had very diverse vegetation. Associated with each subscene were two classified data sets which were compared with each other to create a difference image. A difference image is a matrix of zeros and ones, where the zeros indicate agreement between the two data sets and the ones indicate disagreement. The population parameters were computed from a 100% sample (i.e., total enumeration) of the difference image. The difference image was also repeatedly sampled with various sampling schemes using Monte Carlo methods. A flow diagram of this procedure is displayed in Figure 1.

3.1 Objectives

The objectives of this research were to determine the best (minimum variance) unbiased sampling method to use on a given vegetation environment. This vegetation environment was then related to a pattern of classification error. Once the pattern of error was known, it was then possible to relate this sampling method to other areas of similar patterns of classification error.

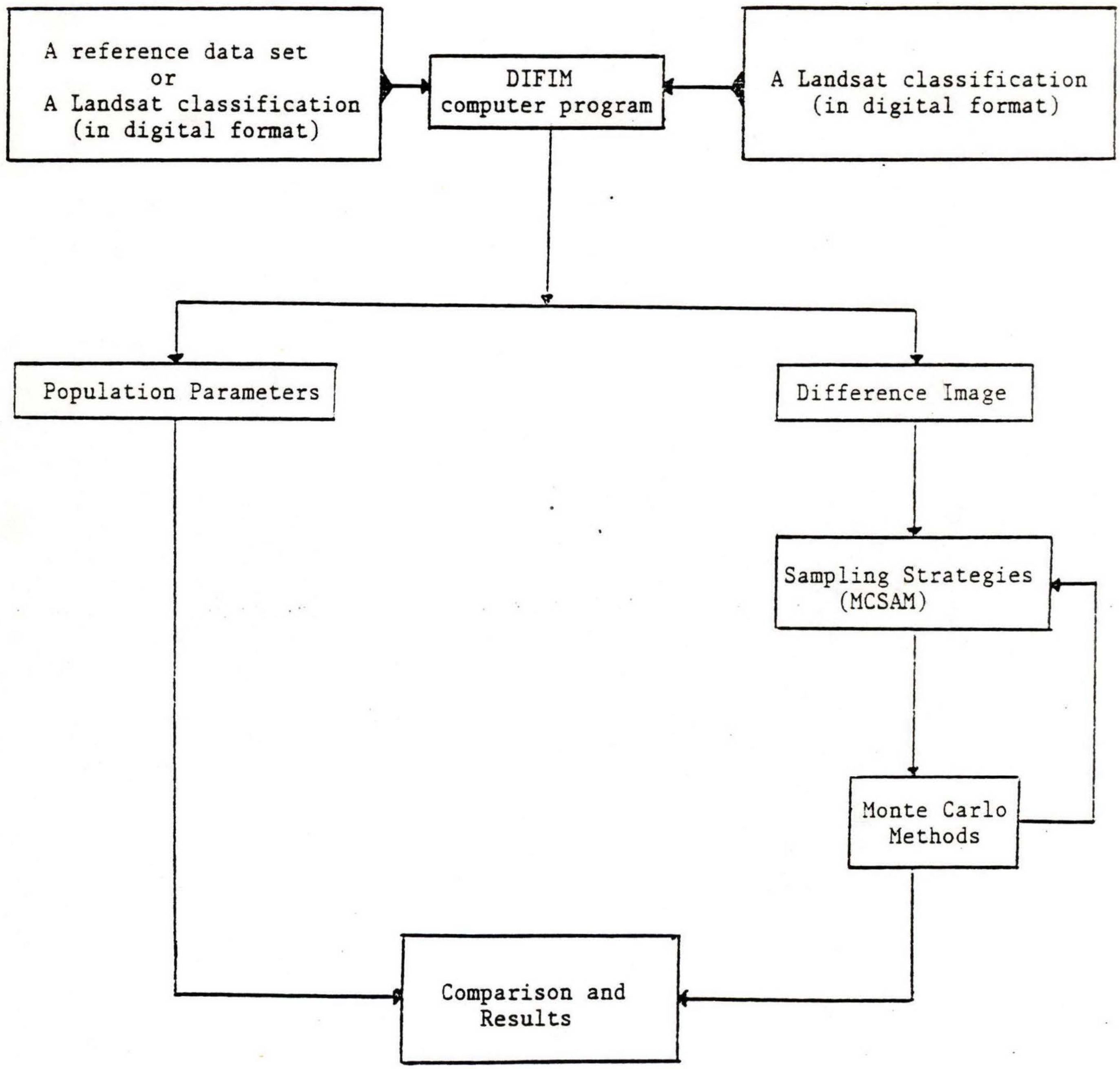

Figure 1. Flow diagram of sampling simulation procedure.

3.2 Study Areas

3.2.1 Forest Land Environment

The forest land study area that was used in this project is the Lolo Creek area located in western Montana. The Bitteroot mountains are the dominant physical feature of the area with elevations ranging from 3,000 feet to 9,200 feet. Average precipitation varies between 50 and 66 centimeters per year. The vegetation of the area is characterized by intermountain forest species.

The subscene chosen for use in this project was the Garden Point 7½ minute quadrangle. This subscene was classified using a 60 meter pixel and resulted in 12 land cover categories. Four of the land cover categories were roads while the other eight were vegetation types.

3.2.2 Rangeland Environment

The rangeland study that was used in this project is located in the northwest corner of Arizona in Mojave County. The area is approximately 1,000,000 hectares in size and is representative of a southwestern desert environment. The Colorado River is the major drainage for the region. The area has a climate characterized by light precipitation, moderate temperatures, plentiful sunshine and low humidity. The vegetation varies from creosote bush and blackbrush at lower elevations to pinyon-juniper and ponderosa pine at higher elevations. The rangeland subscene chosen out of this study area was the Lizard Point 7½ minute quadrangle. This subscene was classified into nine land cover categories. The pixel size used here was 50 meters.

3.2.3 Agricultural Land Environment

The agricultural land study area that was used in this project is the Umatilla Basin which occupies approximately 1.6 million acres in northcentral Oregon. This region is bounded to the north by the Columbia River. The area is characterized by an arid climate averaging less than 10 inches of precipitation per year.

Center pivot irrigation is the major type of irrigation used in the northern section of the basis. It is in this area that a subscene was taken for study in this project. Data from the Clarke 7½ minute quadrange was available in Landsat classification and digitized reference data form. The classification was performed using a pixel size of one acre.

3.3 Data

At least one Landsat classification was available for each subscene. For the forest and range study areas two Landsat classifications were available. The forest study area had one classification performed using DMA terrain data with the Landsat data while the other classification used DEM terrain data along with Landsat. The range study area had one classification performed using DMA terrain data along with the Landsat data while the other classification was based on the Landsat data alone.

The agriculture study area only had one Landsat classification. The other data set used was a reference data set derived from digitizing photography and land surveys.

3.4 Procedure

Once all the data was in digital format, a difference image was generated for each subscene using the computer program, DIFIM. This program processed the two corresponding data sets for each subscene pixel by pixel. When the two corresponding pixels were classified the same, a zero was stored in that place in the output image. If the two corresponding pixels were classified differently, then a one was stored in that place in the output image. Therefore, an output image of zeros and ones was created and called the difference image.

The difference image was then used to generate the population parameters for each subscene. Since the population (i.e., the subscene) was binomially distributed (i.e., a matrix of zeros and ones), the parameters of interest were the size of the population, N, the proportion of correct responses, P, and the variance. The population parameters were also calculated within the DIFIM program.

After these calculations were completed each subscene was repeatedly sampled using Monte Carlo methods and different sampling strategies. These sampling simulations were performed by a computer program called MCSAM. The required inputs for this program were the sampling scheme, the sample size, and the number of repetitions. The outputs of this program were the sample mean, sample variance, and the

number of times the population mean was not contained within the sample confidence interval. For cluster sampling the outputs also included a measure of relative efficiency and the intra-cluster correlation coefficient.

3.5 Results

As previously mentioned, all the results for this research have not been completed. Some preliminary results are given below.

3.5.1 Difference images

The difference images created for each vegetation environment are in Figures 2-4. Note that the yellow shows the areas of agreement between the two data sets while the blue represents pixels of disagreement. Also notice the patterns of error for each vegetation environment.

3.5.2 Intra-cluster correlation coefficients

When using cluster sampling the effects of the cluster need to be measured. A measure of the homogeneity of the cluster is called ROH, intra-cluster correlation. The more homogeneous a cluster the greater the value of ROH. Intuitively one would like the cluster to be as diverse (i.e., heterogeneous) as possible so as to gain maximum information. Therefore it is desirable for ROH to approach zero. Figure 5 shows a plot of average ROH vs. cluster size for each of the vegetation environments.

Figure 2. Difference image for agricultural environment.

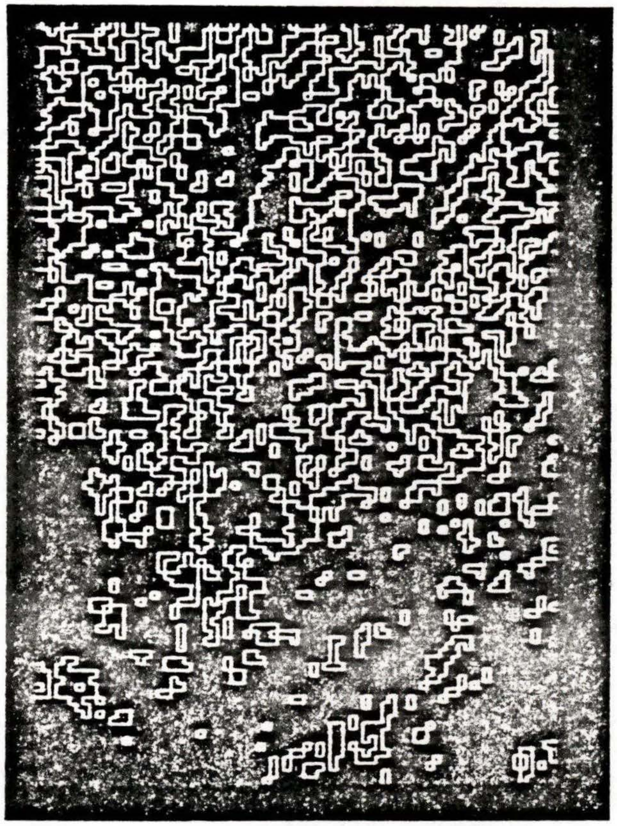

Figure 3. Difference image for range environment.

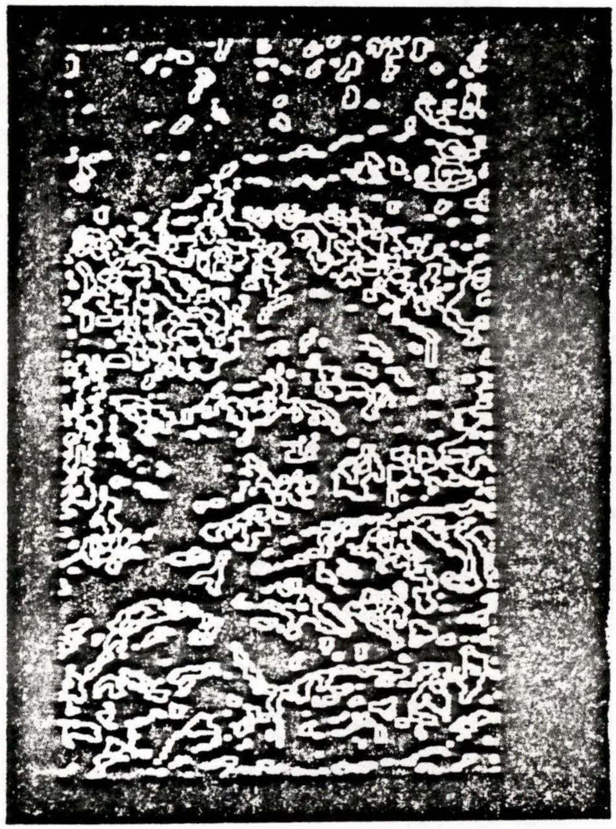

Figure 4. Difference image for forest environment.

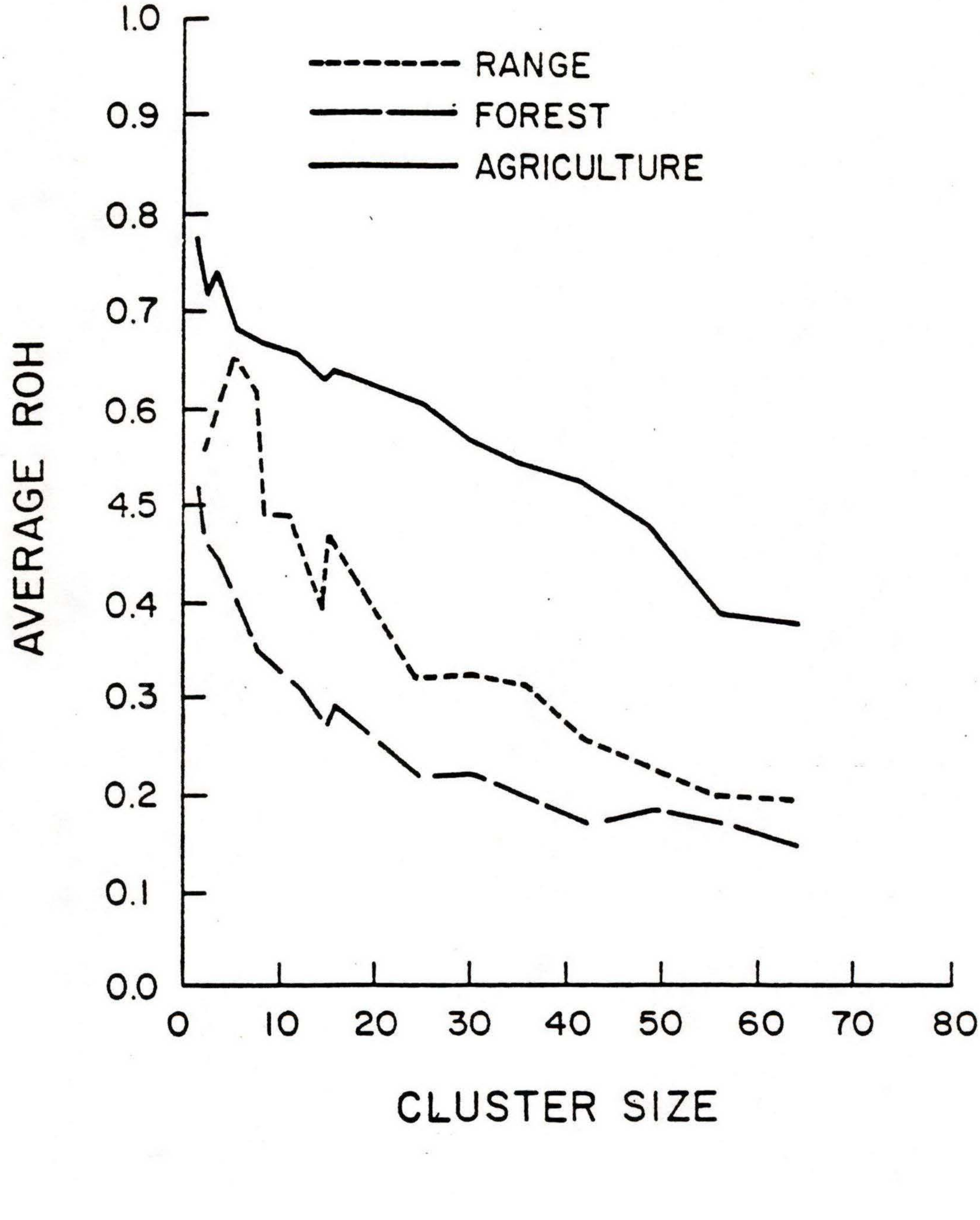

Figure 5. A plot of average ROH vs. cluster size for each vegetation environment.

3.6 Conclusions

As expected the agriculture environment was the most homogeneous because of the large field sizes, while the forest environment was the most heterogeneous. The range environment had a mixture of large areas and small diverse areas and therefore fell somewhere between the agriculture and forest sites. These spatial patterns can be seen by looking at the difference images and also in the plot of ROH vs. cluster size. Remember that a large value of ROH (i.e., close to one) means that the cluster is more homogeneous. Therefore, as seen in Figure 5, the agriculture environment has the largest ROH while the forest site has the smallest.

Also the plot of ROH vs. cluster size dictates some guidelines on what cluster sizes to use. Note that between 0 and 20 pixels/cluster ROH decreases rather quickly while after around 20 pixels/cluster the improvement (i.e., decrease) in ROH occurs more slowly. This result dictates that large cluster sizes may not be gaining more information while costing more time and money to be researched. Therefore, despite the theoretical notion that ROH should be made to go to zero, it is more practical to use reasonable cluster sizes based on this plot and some economic information.

3.7 Further Work

There is a great deal of additional work to be done in sampling simulation. This project has just begun and we hope to accomplish a

great deal more in the next year. Additional sampling schemes need to be investigated and new data sets collected. A possible new data set that contains both a Landsat classification and a reference map is a section of the San Juan National Forest in Colorado. Further investigation in this area can lead to advances in accuracy assessment procedures.

4.0 Literature Cited

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Appendix A

FORTRAN COMPUTER PROGRAM KAPPA

KAPPA


```
//WAIFIV        ,PAGES=35
C               ************************************************
C               *                                              *
C               *   KAPPA WAS WRITTEN AND DOCUMENTED BY        *
C               *         RUSSELL G. CONGALTON                 *
C               *         DEPT. OF FORESTRY, VPI&SU            *
C               *         JULY  1979                           *
C               *                                              *
C               ************************************************
C
C
C  ************************************************************************
C  *                                                                      *
C  * THIS PROGRAM WAS DESIGNED TO TEST FOR SIMILAR DEGREES OF AGREEMENT  *
C  * BETWEEN TWO OR MORE SQUARE ERROR MATRICES                           *
C  *                                                                      *
C  * ME     = THE NUMBER OF TABLES OR MATRICES TO BE COMPARED            *
C  * NR     = NUMBER OF ROWS; ALSO THE NUMBER OF COLUMNS SINCE THE       *
C  *          MATRIX IS SQUARE                                            *
C  * X(I,J) = THE VALUE IN THE MATRIX FOR ROW I AND COLUMN J             *
C  *                                                                      *
C  *                                                                      *
C  ************************************************************************
C
C
      REAL KHAT,LCL
      DIMENSION X(20,20),SXR(20),SXC(20),SD(20),VARNCE(20)
      DIMENSION UCL(20),LCL(20),KHAT(20),STAT(20,20)
      L=20
      M=0
      K=1
C
```

```
      READ(5,10) MF
   10 FORMAT(I2)
C
  100 DO 200 I=1,L
      SXR(I)=0.0
      SXC(I)=0.0
      DO 300 J=1,L
  300 X(I,J)=0.0
  200 CONTINUE
C
      READ(5,20) NR
   20 FORMAT(I2)
      DO 400 I=1,NR
      READ(5,30) (X(I,J),J=1,NR)
   30 FORMAT(12(F6.0))
  400 CONTINUE
      READ(5,31)
   31 FORMAT('AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA')
C
      WRITE(6,999)
  999 FORMAT('1')
      WRITE(6,31)
      WRITE(6,32)
   32 FORMAT(1X,'*************************************************'///)
      WRITE(6,34)
   34 FORMAT(////,1X,'THE ORIGINAL ERROR MATRIX IS:')
      WRITE(6,35)
   35 FORMAT(1X,'______________________________'/)


      DO 450 I=1,NR
      WRITE(6,36) (X(I,J),J=1,NR)
   36 FORMAT(20(1X,F6.0))
  450 CONTINUE
C
```

```
      XN=0.0
      DO 500  I=1,NR
      DO 600  J=1,NR
      SXR(I)=SXR(I)+X(I,J)
      SXC(J)=SXC(J)+X(I,J)
  600 CONTINUE
      XN=XN+SXR(I)
  500 CONTINUE
      TH1=0.0
      TH2=0.0
      TH3=0.0
      TH4=0.0
      DO 700  I=1,NR
      TH1=TH1+X(I,I)
      TH2=TH2+SXR(I)*SXC(I)
      TH3=TH3+X(I,I)*(SXR(I)+SXC(I))
      DO 800  J=1,NR
      TH4=TH4+X(I,J)*(SXR(I)+SXC(J))**2
  800 CONTINUE
  700 CONTINUE
      TH1=TH1/XN
      TH2=TH2/(XN**2)
      TH3=TH3/(XN**2)
      TH4=TH4/(XN**3)
      KHAT(K)=(TH1-TH2)/(1.-TH2)
      VARNCE(K)=(TH1*(1.-TH1)/((1.-TH2)**2)+(2.*((1.-TH1)*(2.*TH1*TH2-TH
     A3)))/((1.-TH2)**3)+(1.-TH1)**2 *(TH4-4.*TH2**2)/(1.-TH2)**4)/XN
      SD(K)=SQRT(VARNCE(K))
      ZSTAT=KHAT(K)/SD(K)
C
C THE STEPS THAT FOLLOW CALCULATE THE 95% CONFIDENCE INTERVAL FOR KHAT
C
      UCL(K)=KHAT(K)+1.96*SD(K)
      LCL(K)=KHAT(K)-1.96*SD(K)
      WRITE  (6,40)
   40 FORMAT(///,1X,'LOWER LIMIT',4X,'KHAT',4X,'UPPER LIMIT')
      WRITE(6,45)
   45 FORMAT(1X,'___________',4X,'____',4X,'___________'/)
      WRITE(6,50) LCL(K),KHAT(K),UCL(K)
   50 FORMAT(3X,F8.5,3X,F8.5,3X,F8.5,///)
      WRITE  (6,51)
   51 FORMAT  (5X,'TH1',7X,'TH2',7X,'TH3',7X,'TH4',7X,'VARIANCE')
      WRITE  (6,52)
   52 FORMAT  (5X,'___',7X,'___',7X,'___',7X,'___',7X,'________',/)
      WRITE  (6,53) TH1, TH2, TH3, TH4, VARNCE(K)
   53 FORMAT  (2X,4(F8.6,2X),2X,F10.8,///)
      WRITE  (6,54) ZSTAT
```

```
   54 FORMAT (5X,'THE Z STATISTIC IS:',F10.5)
      K=K+1
      M=M+1
      IF(M.LT.ME) GO TO 100
      WRITE(6,900)
  900 FORMAT('1','SUMMARY TABLE AND COMPARISONS')
      WRITE(6,910)
  910 FORMAT(1X,'*****************************'////)
      WRITE(6,920)
  920 FORMAT(1X,'MATRIX',2X,'LOWER LIMIT',4X,'KHAT',4X,'UPPER LIMIT')
      WRITE(6,930)
  930 FORMAT(1X,'______',2X,'___________',4X,'____',4X,'___________'//)
      DO 940 K=1,ME
      WRITE(6,950) K,LCL(K),KHAT(K),UCL(K)
  950 FORMAT(4X,I2,5X,F8.5,3X,F8.5,3X,F8.5)
  940 CONTINUE
      WRITE(6,960)
  960 FORMAT(////////)
      WRITE (6,1000)
 1000 FORMAT (1X,'COMBINATION',20X,'TEST STATISTIC')
      WRITE (6,1001)
 1001 FORMAT (1X,'___________',20X,'______________',//)
      N=ME-1
      DO 1300 I=1,N
      K=I+1
      DO 1400 J=K,M
      SQVAR=SQRT(VARNCE(I)+VARNCE(J))
      STAT(I,J)=(KHAT(I)-KHAT(J))/SQVAR
      WRITE (6,1200) I,J,STAT(I,J)
 1200 FORMAT (2X,I3,1X,I3,24X,F8.4,/)
 1400 CONTINUE
 1300 CONTINUE
      WRITE(6,1500)
 1500 FORMAT('1')
      STOP
      END

//DATA
```

APPENDIX B

RESULTS OF ACCURACY ASSESSMENT OF THE SAN JUAN NATIONAL FOREST R2MAP LAND COVER CLASSIFICATION

The Kappa statistic, κ, was calculated for each of the eight matrices arising from contract classification east and west (CCE, CCW), data base classification east and west (DBE, DBW), abbreviated contract classification east and west (ACE, ACW), and abbreviated data base classification east and west (ADE, ADW). The resulting Kappa's, variances, and 95% confidence intervals for Kappa are displayed in Table B.1. The confidence intervals are displayed graphically in Figure B.1. Kappa was significantly greater than zero ($\alpha = .05$) for all eastern classification, and was not significantly different from zero ($\alpha = .05$) for all western classification.

Classification accuracy as measured by Kappa was very low for all matrices. The low Kappa values, however, may not be entirely due to low classification accuracy. The large number of "NO SYMBOL" categories in each matrix and the small sample sizes, particularly in the western matrices, also contribute to the low Kappa's. The extent of this contribution, however, cannot be assessed mathematically.

Comparisons were made of the Kappa's for contract classification versus data base classification by location (east and west), for eastern classification versus western classification by classification type (contract and data base), and for abbreviated classification versus full classification by location (east and west). The results appear in Table B.2. Kappa's for the stated comparisons were not significantly different ($\alpha = .05$) in any instance.

Further accuracy analyses of the matrices can be conducted to evaluate their usefulness for a particular purpose. For example, a weighting scheme can be used to emphasize categories of interest to wildlife managers while reducing the importance of forest and range categories. Another way to accomplish the same end without weights is to lump together categories whose value to a function is minimal. It is very possible that these maps are quite suitable for one function while being inappropriate for another. These types of analyses can be performed quite easily and quickly if the necessary information (weights and/or categories to be lumped) is made available.

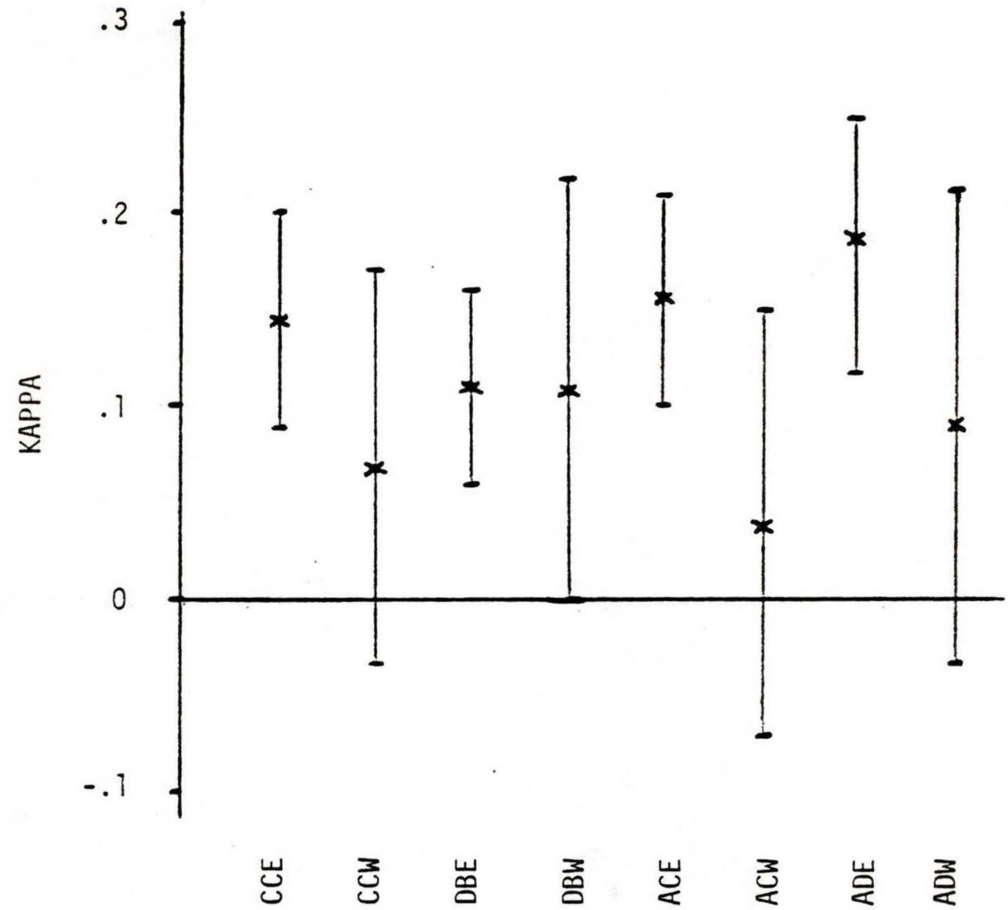
Table B.1. Kappa (κ), variance of Kappa, and 95% confidence interval for Kappa for each classification matrix.

Matrix	κ	σ_{κ}^{2}	95% Confidence Interval[2/] (Lower Limit,	Upper Limit)
CCE	.149	.00076	.094,	.203
CCW	.071	.00281	-.033,	.175
DBE	.109	.00070	.058,	.161
DBW	.108	.00317	-.002,	.218
ACE	.153	.00081	.097,	.208
ACW	.039	.00312	-.071,	.148
ADE	.186	.03260	.122,	.249
ADW	.093	.06179	-.028,	.214

1/ See text for explanation of matrix identification abbreviations.

2/ Confidence interval calculated as $\kappa \pm 1.96\sigma_{\kappa}$.

Figure B.1. Graphical representation of 95% confidence intervals for Kappa for each classification matrix.[1/]



1/ See text for explanation of matrix identification abbreviations.

Table B.2. Tests for significant differences between Kappa's from selected matrices.[1/]

Matrices	Z Value [2/]
Contract classification versus data base classification by location	
CCE vs. DBE	1.02
CCW vs. DBW	0.48
ACE vs. ADE	0.76
ACW vs. ADW	0.65
Eastern classification versus western classification by classification type	
CCE vs. CCW	1.30
DBE vs. DBW	0.02
ACE vs. ACW	1.82
ADE vs. ADW	1.32
Abbreviated classification versus full classification by location	
CCE vs. ACE	0.11
CCW vs. ACW	0.42
DBE vs. ADE	1.81
DBW vs. ADW	0.18

1/ See text for explanation of matrix identification abbreviations.

2/ Test statistic $Z = \frac{\kappa_A - \kappa_B}{\sqrt{\sigma^2_{\kappa A} + \sigma^2_{\kappa B}}}$; Z must exceed 1.96 for the κ's to be significantly different ($\alpha = .05$).

APPENDIX C

ESTIMATING SAMPLE SIZE REQUIREMENTS FOR ACCURACY ASSESSMENT USING KAPPA

Sample size formula

Sample size calculations for estimating Kappa are based on the confidence interval formula

$$\kappa \pm Z \cdot \sigma_\kappa$$

where κ is Kappa, σ_κ is the standard deviation of Kappa, and Z is a standard normal deviate. The value of Z may be selected to yield an interval of the desired confidence level.

We will require the estimate of κ to be within $\pm E$ of the true κ, where E is the allowable limit of error. This is equivalent to saying

$$E = Z\sigma_\kappa .$$

Since the functional form of σ_κ is extremely complex, an approximate, simpler form of σ_κ will be used. This form is

$$\sigma_\kappa = \sqrt{\frac{p_0(1 - p_0)}{N(1 - p_c)^2}}$$

where p_0 is the actual agreement in the matrix, p_c is the chance agreement in the matrix, and N is the sample size.

The expression for E may now be rewritten as

$$E = Z \sqrt{\frac{p_0(1 - p_0)}{N(1 - p_c)^2}}$$

which leads to

$$N = \frac{p_0(1 - p_0)}{(1 - p_c)^2} \cdot \frac{Z^2}{E^2}$$

With selection of Z and E and estimation of p_0 and p_c this equation may be used to estimate sample size. This equation is equivalent to the statement: Unless a chance error has occurred, the chance being controlled by Z, the estimate of κ will be within $\pm E$ of the true κ.

To implement the sample size equation p_0 and p_c must be estimated. The value p_0 is the proportion of sample observations lying on the main diagonal of the matrix. This fraction may be estimated based on past analysis or an expected result.

The value p_c is calculated as

$$p_c = \sum_{i=1}^{t} p_{i+}p_{+i}$$

where t is the number of rows (and columns) in the matrix, p_{i+} is the proportion of observations assigned to category i by the classification algorithm, and p_{+i} is the proportion of observations belonging to reference data category i. (The definitions of p_{i+} and p_{+i} may be switched by transposing the matrix.)

The proportion of observations in the i^{th} reference data category, p_{+i}, may be estimated using the assumed proportion of land area in the coverage area that is in category i. While p_{i+} cannot usually be reliably estimated prior to sampling, it is reasonable to assume that adequate classification would result in p_{i+} that is approximately equal to p_{+i}. Therefore, p_c can be rewritten as

$$p_c = \sum_{i=1}^{t} p_{+i}^2.$$

These estimates of p_0 and p_c may be combined to estimate σ_κ^2. The given approximation for σ_κ^2 has been shown to be generally larger than the true variance, although this will not be true in every case. Therefore the calculated sample size, N, will generally be more than sufficient to attain the desired limit of error.

<u>Example sample size calculation</u>

Unless a 1 in 20 chance occurs, we wish to estimate κ to within $\pm.1$. The area in question consists of only three distinct categories: Water (category 1); Forest (category 2); Range (category 3). The proportion of the area in each category is estimated to be:

Category No.	Type	Proportion
1	Water	.2
2	Forest	.3
3	Range	.5

In past analyses of the area approximately 60% of the observations fell on the main diagonal of the matrix.

Now $Z = 1.96$

$E = .1$

$p_0 = .6$

$p_c = (.2)^2 + (.3)^2 + (.5)^2 = .38.$

Therefore

$$N = \frac{(.6)(1 - .6)}{(1 - .38)^2} \cdot \frac{(1.96)^2}{(.1)^2} \stackrel{\sim}{=} 240$$

APPENDIX D

A PROPOSED METHOD FOR ESTIMATING THE RELIABILITY OF CHANGE DETECTION

Maps are often used to measure changes in cover types or land use over an interval of time. If the maps produced at each time were perfectly accurate, changes could be known without error. Most maps, however, contain errors in classification that make change detection subject to error. There are two perspectives from which to examine change; the first is a proportion of area basis, the second is a site specific basis. Change from a proportion of area perspective deals with the change in the proportion of an area assigned to a particular category over time. For example, a map made at time 1 identifies 50% of the covered area as water, while a map of the same area made at time 2 identifies 60% of the area as water. No reference to a particular location is made, although the overall results can be applied to a particular location.

Change from a site specific perspective deals with the change of a particular location from one category to another over time. Site specific change detection is extremely important in some map uses, but is more difficult to handle analytically than change in proportion to area. The following discussion will deal only with change from a proportion of area perspective. Hopefully, experience and insight gained in working with proportion of area change can be used to develop methods of dealing with site specific change.

The method outlined below is only a first step in determining the reliability of change detection. Further research is necessary before this method is implemented operationally.

Define two error matrices A and B, where matrix A is produced from mapping an area at time 1, matrix B is produced by mapping the same area at a subsequent time 2, and each matrix is comprised of the same categories. Let p_{i+}^{A} and p_{i+}^{B} denote the proportion of sample observations assigned to category i at times 1 and 2, respectively.

Both p_{i+}^{A} and p_{i+}^{B} are subject to errors of omission and commission in the classification. If some measure of the reliability of p_{i+}^{A} and p_{i+}^{B} could be determined, the reliability of the change over time could be determined.

The agreement measure Kappa, κ, previously defined in this report, provides a type of reliability measure for an entire error matrix. A category specific measure of agreement, similar to Kappa, called κ_i, is defined by Bishop <u>et al</u>., 1975, as

$$\kappa_i = \frac{p_{ii} - p_{i+}p_{+i}}{p_{+i} - p_{i+}p_{+i}}$$

where p_{ii} is the proportion of observations in the i^{th} classification category and i^{th} reference data category, p_{i+} is the proportion of observations in the i^{th} reference data category, and p_{+i} is the proportion of observations in the i^{th} classification category. (The identity of the rows and columns can be exchanged by transposing the matrix.) κ_i has the same characteristics as κ in that it accounts for both chance and actual agreement and has the same range.

If interest is restricted to κ_i such that $0 \leq \kappa_i \leq 1$, then κ_i can serve as a reliability measure of a particular p_{i+}. It is reasonable to restrict attention to κ_i in this range since negative agreement in an error matrix is an undesirable and hopefully unusual occurrence.

The reliability of the change from p_{i+}^A to p_{i+}^B can now be calculated in the same manner as the reliability of a parallel circuit. In the parallel circuit the two components, in this case p_{i+}^A and p_{i+}^B, have individual reliabilities, κ_i^A and κ_i^B, and the reliability of the entire circuit is calculated as $\kappa_i^A \cdot \kappa_i^B$. This value can be calculated for each category resulting in a matrix of reliabilities of changes from a category at time 1 to a category at time 2.

The example in Figure D.1. shows the original error matrices A and B at times 1 and 2, respectively, their associated κ_i's, and the matrix of reliabilities of change. This last matrix can be evaluated cell by cell, or an overall reliability can be found by averaging the cell entries. A further refinement in overall reliability calculation can be achieved by weighting each cell value by importance.

Further research is needed to determine if κ_i can truly be interpreted as a reliability measure, what consequences must be accepted when some κ_i are less than zero, whether this method can be extended to cover unmatched categories between the two maps, and if the method can be used to determine site specific change reliability.

Figure D.1. Example of the proposed methods of determining reliability of change detection.

Error Matrix A

Reference Data

Classification	1	2	3	p_{i+}^{A}	κ_i^{A}
1	.31	.03	.02	.36	.75
2	.02	.20	.05	.27	.61
3	.04	.05	.28	.37	.68

Error Matrix B

Reference Data

Classification	1	2	3	p_{i+}^{B}	κ_i^{B}
1	.14	.02	.05	.21	.54
2	.03	.26	.02	.31	.73
3	.05	.04	.39	.48	.71

Reliability Matrix

		κ_1^{B} .54	κ_2^{B} .73	κ_3^{B} .71
κ_1^{A}	.75	.41	.55	.53
κ_2^{A}	.61	.33	.45	.43
κ_3^{A}	.68	.37	.50	.48

APPENDIX E

Accuracy Assessment of the San Juan National Forest R2MAP Land Cover Classification

E.1 Introduction

An accuracy assessment was conducted for the San Juan National Forest. Specifically, this included development of error matrices to supplement the preliminary evaluation made by Lockheed Electronics Company,* Inc. Lockheed has used Landsat digital data to map land cover/vegetation for the entire San Juan National Forest from two adjacent scenes according to a classification system agreed to by the Forest Service. Personnel at Virginia Tech worked with managers on the San Juan National Forest to determine the accuracy for (a) the east half of the Forest (from the eastern Landsat scene); (b) the west half of the Forest (from the western Landsat scene); (c) using the classification system agreed to in the Lockheed contract; and (d) according to the classification system used in development of the Forest's "R2MAP" digital data base. An explanation for the two classification systems is given in Appendix F. Also the corresponding R2MAP symbols are given in Tables E.1 and E.2.

E.2 Procedure

The following procedure was used to conduct the accuracy assessment:

---

* Mazade, A. V., C. A. Underwood, J. F. Ward, and S. S. Yao. 1979. Remote Sensing and Computer-Based Vegetation Mapping in the San Juan National Forest, Colorado. Final Report LEC-13792, Lockheed Electronics Co., Inc. 60 pp.

Table E.1. The contract land cover categories and the corresponding R2MAP symbols.

Land Cover Categories	Symbol	West half of forest	East half of forest
Aspen/Cottonwood	G	95 A4	$2 A3 94 A4
Aspen/Conifer	BB	No R2MAP Symbol	E2
Ponderosa Pine	A	X5	P1 P3
Spruce-Fir	E	No R2MAP Symbol	S4
Douglas-Fir	C	No R2MAP Symbol	C4 D3
Ponderosa Pine/Oak	Z	F2 F3	No R2MAP Symbol
Conifer/Aspen	AA	No R2MAP Symbol	H4
Oak	K	O1 O4 O2 O3 L2	O4 O3 O2
Pinyon/Juniper	M	J4	J1 Ø2 &1
Oak/Conifer	CC	T3	Z5
Rock/Barren	U	Y5 Ø5 /5 A5 V5 =5]5 @5 A5 N5	X5 R5
Willow	O	No R2MAP Symbol	]5
Mixed Brush	Q	B4 B3	No R2MAP Symbol
Mesic	R	M5	No R2MAP Symbol
Grass	Y	Z5 G5 <5	G5 =5 /5
Alpine	X	No R2MAP Symbol	M5 :5
Rocky/Grass	DD	6	I5 %5 Ø5
Water	V	W5	W5 #5
Other	W	U5 %5 #5	@5 <5

Table E.2. The data base land cover categories and the corresponding R2MAP symbols.

Land Cover Categories	Symbol	West half of forest	East half of forest
Cottonwood (>30%)	I	No symbol	No symbol
Aspen (>30%)	G	95 A4	$2 A3 94 A4 #4
Ponderosa Pine (>30%)	A	F3	P1 P3
Spruce-Fir (>30%)	E	No symbol	S4
Douglas-Fir (>30%)	C	No symbol	C4 D3
Oak (>30%)	K	04 03 02 T3	04 03 02
Pinyon Juniper (>30%)	M	J4	No symbol
Cottonwood (10-30%)	J	No symbol	]5
Aspen (10-30%)	H	No symbol	E2
Ponderosa Pine (10-30%)	B	X5 F2	Z5
Spruce-Fir (10-30%)	F	No symbol	No symbol
Douglas-Fir (10-30%)	D	No symbol	No symbol
Oak (10-30%)	L	L2 01	No symbol
Pinyon Juniper (10-30%)	N	No symbol	J1 02 &1
Rock/Barren	U	V5 =5]5 @5 A5 N5 Y5 Ø5 R5 /5	X5 R5
Willow	O	No symbol	No symbol
Mixed Brush	P	B4 B3	No symbol
Sage	Q	No symbol	No symbol
Meadow	R	M5	M5
Sonoran	S	G5	Ø5

Table E.2. (Continued)

Land Cover Categories	Symbol	West half of forest	East half of forest
Montane	T	Z5 <5 6	G5 =5
Alpine Xeric	Y	No symbol	I5 %5 :5
Alpine Mesic	X	No symbol	/5 -5
Water	V	W5	W5 #5
Other	W	U5 %5 #5	@5 <5

Step I.

The staff of the San Juan National Forest visited many areas on the groundand related them to the symbols printed on the R2MAPS. This permitted the local resource managers to develop a detailed definition of the Landsat classification categories. Also, the field crews became familiar with characteristics of each category as they appear on color infrared aerial photography. A set of "photo examples" for each category was made for use by all the photo interpreters. This should help assure consistency in the ground reference data collection.

Step II.

Computer printouts which summarize the number of acres of each Landsat category classified on each quad (from R2MAP) was produced. The forest boundary was used to screen only those R2MAP cells within the National Forest. All private lands within the forest were delted. This permitted the forest to be stratified into the various Landsat categories which were each sampled proportionally. (Note that the classification was sampled and not the ground cover.) After the relative proportions of each strata were determined the number of pixels (3 ac. cells) within each quad that should be sampled by each category were computed.

Step III.

A list of random coordinates were compiled for use in selecting sample cells within each individual quad. Cells were sampled without

replacement until the desired number of cells needed for each category was reached. The location of each cell kept and used in the evaluation were transferred to its corresponding location on the topographic map and assigned a sample number.

Step IV.

Each R2MAP cell selected was next transferred from the topographic map to the 1:30,000 scale 9 x 18 inch aerial photography (flown in September, 1981) and delineated on a transparent overlay fastened to the photo. No indication of how Landsat classified each cell was put on the overlay. (This would bias the photo interpretation.) Only the sample number was next to each cell.

Step V.

Three independent photo interpreters assigned a Landsat category to each sample block according to the category definitions and "photo examples" developed in step I. Complete interpretation agreement among the three interpreters was mandatory. All differences in category assignment were resolved. This required the photo interpreters to meet and "negotiate" a proper interpretation.

Step VI.

Virginia Tech designed a technique and administered a test to assure that consistent photo interpretation was achieved. Also, Virginia Tech

designed the forms for recording all data, reviewed the category definitions and all procedures. Finally, Virginia Tech compiled and reported the final error matrix for the R2MAP accuracy. The data were compiled so that one matrix was produced for the east portion (i.e., east Landsat scene) and one for the west (i.e., west Landsat scene) under each classification system. These matrices are given in Tables E.3, E.4, E.5, E.6, E.7, E.8, E.9, and E.10. Note that there were several instances where there was no R2MAP symbol which corresponds to the land cover categories under both the contract or data base classification systems.

E.3 Sample Size Determination

Map accuracy was determined using the $\hat{K}$ statistic (Bishop, Fienberg, and Holland, 1975):

$$\hat{K} = \frac{N \sum_{i=1}^{n} x_{ii} - \sum_{i=1}^{n} x_{i+} x_{+i}}{N^2 - \sum_{i=1}^{n} x_{i+} x_{+i}}$$

where

N = number of observations,

n = number of categories,

x_{ii} = number of observations classified as category i by both photo interpretation and the Landsat classification algorithm,

x_{i+} = number of observations classified as category i by photo interpretation,

x_{+i} = number of observations classified as category i by the Landsat classification algorithm.

Table E.3. Contrast Classification - East Half.

REFERENCE DATA (PHOTO INTERPRETATION)

CLASSIFICATION (R2 MAP SYMBOL)

	G	BB	A	E	C	Z	AA	K	M	CC	U	O	Q	R	Y	X	DD	V	W	TOTAL
$2 A3 A4 94	8	1			1									1	2					13
E2	5	2	2	1	1	1	1	3							2					18
P1 P3		1	2	5	2						2	1	1		1	1	1			17
S4				9																9
C4 03	3	7	12	26	7	1	6	2		1					2					67
NO SYMBOL																				0
H4	7			5	4			1							1					18
04 03 02	7	1	2	3	2		1	5							8	1				30
J1 02 81			3	3			1	1	1		1	1	1	1	1	1				15
Z5							1													1
X5 R5				2							9	2				1			1	15
]5																				0
NO SYMBOL																				0
NO SYMBOL																				0
G5 =5 /5	1		1									1			3		1			7
M5 :5								1				1								2
I5 %5 ©5				1							3	2								6
W5 •5				2							1							1		4
@5 <5												1								1
TOTAL	31	12	22	57	17	2	10	13	1	1	16	9	2	2	20	4	2	1	1	223

Table E.4. Contract Classification - West Half.

REFERENCE DATA (PHOTO INTERPRETATION)

CLASSIFICATION (R2 MAP SYMBOL)	G	BB	A	E	C	Z	AA	K	M	CC	U	O	Q	R	Y	X	DD	V	W
95 A4																			
NO SYMBOL																			
X5																			
NO SYMBOL																			
NO SYMBOL																			
F2 F3			4					2							1				
NO SYMBOL																			
<2 01 04 02 03								4			1								
J4										1									
T3								1											1
]5 V5 Y5 Ø5 N5 @5 *5 /5 A5 R5								1											
NO SYMBOL																			
B4 B3								1	1										
M5																			
Z5 G5 <5		1	1					3	4	1					1				
NO SYMBOL																			
6																			
W5																			
U5 %5 #5																			

Table E.5. Abbreviated Contract Classification - East Half.

REFERENCE DATA

CLASSIFICATION (R2 MAP SYMBOL)	G	BB	A	E	C	AA	K	M	CC	U	O	Y	X	DD	V	W
$2 A3 A4 94	8	1			1							2				
E2	5	2	2	1	1	1	3					2				
P1 P3		1	2	5	2					2	1	1	1	1		
S4				9												
C4 D3	3	7	12	26	7	6	2		1			2				
H4	7			5	4		1					1				
O4 O3 O2	7	1	2	3	2	1	5					8	1			
J1 Ø2 &1			3	3		1	1	1		1	1	1	1			
Z5						1										
X5 R5				2						9	2		1			1
]5																
G5 =5 /5	1		1								1	3		1		
M5 :5							1				1					
I5 %5 Ø5				1						3	2					
W5 #5				2						1					1	
@5 <5											1					

Table E.6. Abbreviated Contract Classification - West Half.

REFERENCE DATA

CLASSIFICATION (R2 MAP SYMBOL)

	G	A	Z	K	M	CC	U	Q	R	Y	DD	V	W
95 A4													
X5													
F2 F3		4		2						1			
<2 O1 O4 O2 O3				3			1	1					
J4						1							
T3				1									1
]5 V5 Y5 Ø5 N5 5 *5 /5 A5 R5				1									
B4 B3				1	1								
M5													
Z5 G5 <5		1		3	2	1				1			1
6													
W5													
u5 %5 #5													

Table E.7. Data Base Classification - East Half.

REFERENCE DATA (PHOTO INTERPRETATION)

CLASSIFICATION (R2 MAP SYMBOL)	I	G	A	E	C	K	M	J	H	B	F	D	L	N	U	O	P	Q	R	S	T	Y	X	V	W	TOTAL
NO SYMBOL																										0
S2 A3 94 H4 A4				5	5	1			1	1											2					31
P1 P3		1	2	5	2						2				1	1	1				1					16
S4				9																						9
C4 D3		9	14	29	9	3			1												2					67
04 03 02		8	2	3	2	5			1		3		2								3					29
NO SYMBOL																										0
]5																										0
E2		6	1	3	1	3			2	2																18
Z5				1																						1
NO SYMBOL																										0
NO SYMBOL																										0
NO SYMBOL																										0
02 B1 J1			3	3							2															6
X5 R5				2							2				7	2							1			15
NO SYMBOL																										0
SYMBOL																										0
NO SYMBOL																										0
M5						1																				1
Ø5															1											1
G5 *5		1	1																	1	1					4
I5 %5 5				1											2	3										6
-5 /5																2					1		1			4
#5 W5				1							1				1									1		4
@5 <5																1										1
TOTAL	0	41	23	61	19	14	1	0	5	3	10	0	2	0	13	10	2	0	0	2	10	1	3	1	1	223

Table E.8. Data Base Classification - West Half.

REFERENCE DATA (PHOTO INTERPRETATION)

CLASSIFICATION (R2 MAP SYMBOL)

	I	G	A	E	C	K	M	J	H	G	F	D	L	N	U	O	P	Q	R	S	T	Y	X	V	W
NO SYMBOL																									
95, A4																									
F3			2																						
NO SYMBOL																									
NO SYMBOL																									
C4 O3 O2 T3						3																			
J4													1												1
NO SYMBOL																									
NO SYMBOL																									
X5 F2			2			2			1																
NO SYMBOL																									
NO SYMBOL																									
<2 O1						2									1										
NO SYMBOL																									
N5,V5,+5,J5,#5 A5,R5,/5,Y5,O5						1																			
NO SYMBOL																									
B4 B3						1	1																		
NO SYMBOL																									
M5																									
G5		1	1			3	2		1				1												
Z5 <5 6						1																			
NO SYMBOL																									
NO SYMBOL																									
W5																									
U5 %5 ⇒5																									

Table E.9. Abbreviated Data Base Classification - East Half.

CLASSIFICATION (R2 MAP SYMBOL) \ REFERENCE DATA	G	A	E	C	K	J	H	B	N	U	R	S	T	Y	X	V	W	TOTAL
S2 A3 H4 A4 94	16		5	5	1		1	1					2					31
P1 P3	1	2	5	2						1			1					12
S4			9															9
C4 D3	9	14	29	9	3		1						2					67
04 03 02	8	2	3	2	5		1						3					24
]5																		0
E2	6	1	3	1	3		2	2										18
Z5			1															1
O2 J1 B1		3	3		1					1		1		1	1			11
X5 R5			2							7					1		1	11
M5																		1
Ø5										1								1
G5 =5	1	1										1	1					4
I5 9.5 :5			1							2								3
/5													1		1			2
W5 #5			1							1						1		3
@5 <5																		0
	41	23	62	19	14	0	5	3	0	13		2	10	1	3	1	1	198

Table E.10. Abbreviated Data Base Classification - West Half.

REFERENCE DATA

CLASSIFICATION (R2 MAP SYMBOL)	G	A	K	M	B	L	U	P	R	S	T	V	W	TOTAL
94 A4														0
F3		2												2
04 03 02 T3			3										1	4
J4						1								1
X5 F2		2	2										1	5
<2 O1			2				1							3
R5 V5 =5]5@5 /5 A5 N5 Y5 Ø5			1											1
B4 B3			1	1										2
M 5														0
G 5	1	1	3	2		1								8
Z5 6 <5			1											1
W5														0
U5 %5 #5														0
TOTAL	1	5	13	3		2	1						2	27

The null hypothesis of $\hat{K}$ equal to zero can be tested statistically using the asymptotic variance. The asymptotic variance of $\hat{K}$, $\hat{\sigma}^2$ ($\hat{K}$), is available, but was not stated here because of its complexity.

The factors affecting the size of $\hat{\sigma}^2$ ($\hat{K}$) that can be controlled by sampling are the number of observations, N, and the number of categories, n. Since the number of categories is set by map requirements, only the number of observations can be controlled.

A small presample was gathered to provide information about the size of the variance for a given sample size in this particular situation. A final sample size for determining overall map accuracy can then be selected using the presample information as a base.

The sources of agreement and disagreement between classification by photo interpretation and by Landsat algorithm can be investigated using the techniques of categorical data analysis (Bishop, Fienberg, and Holland, 1975). Sample sizes necessary for these techniques are fixed by the analysis method rather than by the degree of precision desired; sample sizes below a certain threshhold are simply too low to allow analysis.

The usual sample size required to perform categorical data analysis is five times the square of the number of categories. This sample size is expected to be considerably larger than that required to determine overall map accuracy, but the larger sample size is required if the sources of error in the map are to be identified.

E.4 Summary

The number of samples which were taken (due to personnel time) for the accuracy assessment was too small to give reliable results at any specified precision level. However, it is clear that the R2MAP data (i.e., 3 acre cell category labels) are quite different from the consensus of the three photo interpreters. These errors may in large part be due to misregistration in the Landsat classification. Also, some error could be attributed to the process of resampling the 1 acre Landsat pixels to form the 3 acre R2MAP cell classifications. Analyses of this assessment are given in Appendix B.

The utility of the land cover data in R2MAP for use by the San Juan National Forest will have to be judged by the Forest Service personnel.

APPENDIX F

Explanation of the Two Land Cover Classification Systems used in the San Juan National Forest Accuracy Assessment

Attachment 2

SAN JUAN NATIONAL FOREST
REMOTE SENSING PROJECT

Contract Classification of Cover Classes
for Accuracy Assessment

The following classification system further defines the cover types for which the R2MAP symbols were developed. The original definitions in Exhibit A, p.A-4 of the Remote Sensing and Computer Based Vegetation Mapping in the San Juan National Forest, Colorado. Final Report for USDA/FS Contract 53-82x9-8-2338 October 11, 1978 - September 1, 1979, were followed as closely as possible to maintain as much consistency as possible with the work already completed. The primary problems with the existing definitions was their tendency to overlap. The cover type key presented here will reduce this tendency.

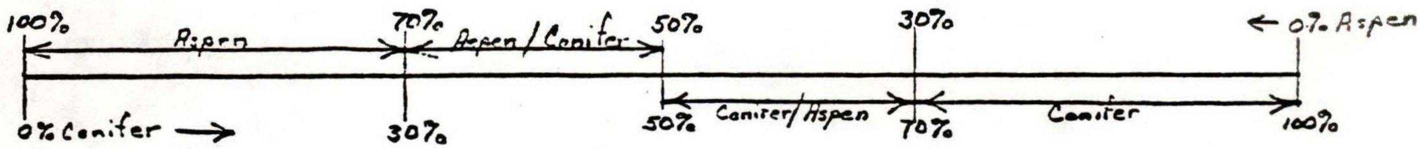
The attached diagram provides a schematic view of the key. These cover classes and cover types apply to 3 acre cells which are the basic unit in R2MAP.

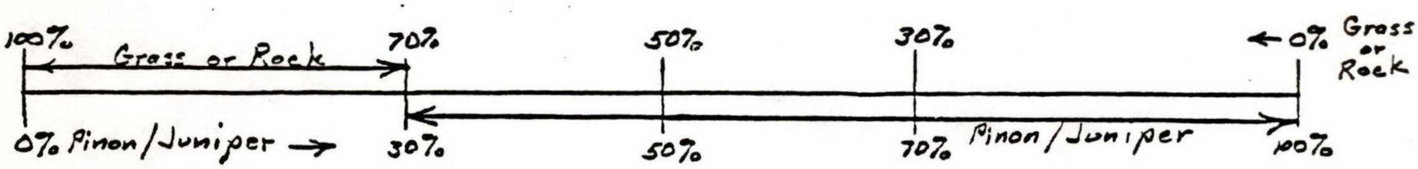
The second attached key is for the Forest data base.

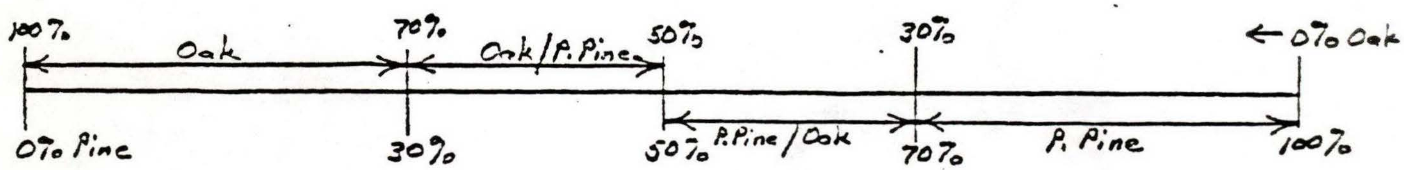
COVER TYPE DIVISIONS

FOREST - Cells with crown cover > 30%

- % refers to % of existing crown or ground cover in a 3 acre cell.

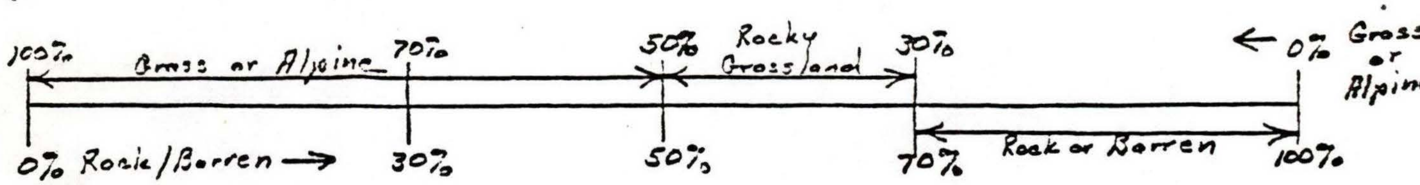


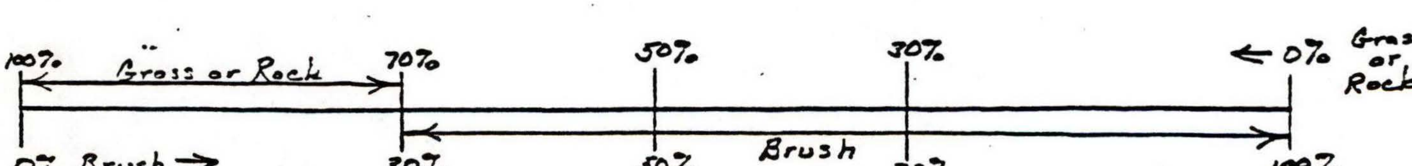




NON FOREST - Cells with < 30%

- % refers to % of the cell not covered by tree crown cover.





Note: Within the forested cover types, species dominance drives the classification system. Between forest and nonforest cover types and within the nonforest types a hierarchical system exists. Forest types override nonforest types. Brush overrides grass types.

SAN JUAN NATIONAL FOREST
Ground Cover Type Key-Contract
(Cover Types are underlined)

I. Lands

IA. Forest

IA1. Commercial

IA1(a). Hardwood

IA1(a)(1). Aspen/Cottonwood

IA1(a)(2). Aspen/Conifer

IA1(b). Conifer

IA1(b)(1). Ponderosa Pine

IA1(b)(2). Spruce-Fir

IA1(b)(3). Douglas-fir

IA1(b)(4). Ponderosa Pine/Oak

IA1(b)(5). Conifer/Aspen

IA2. Non Commercial Forest

IA2(a). Oak

IA2(b). Pinon/Juniper

IA2(c). Oak/Conifer

IB. Non Forest

IB1. Rock Barren

IB2. Brush

IB2(a). Willow

IB2(b). Mixed Brush (Sage

IB3. Grass

IB3(a). Mesic (Meadows)

IB3(b). Grass (Sonoran & Montane

IB3(c). Alpine (Xeric & Mesic)

IB3(d). Rocky/Grass

II. Water

III. Snow

IV. Shadow

SAN JUAN NATIONAL FOREST
Ground Cover Type Key - Contract
(Cover types are underlined)

- I. Land
  - A. Forest (>30% Tree Crown Cover)
    - 1. Commercial
      - (a) Hardwood
        - (1) <u>Cottonwood/Aspen</u>
        - (2) <u>Aspen Conifer</u>
      - (b) Conifer
        - (1) <u>Ponderosa Pine</u>
        - (2) <u>Spruce Fir</u>
        - (3) <u>Douglas Fir</u>
        - (4) <u>Ponderosa Pine/Oak</u>
        - (5) <u>Conifer/Aspen</u>
    - 2. Non Commercial
      - <u>(a) Oak</u>
      - <u>(b) Pinon/Juniper</u>
      - <u>(c) Oak/Conifer</u>
  - B. Non Forest (<30% Tree Crown Cover)
    - <u>1. Rock/Barren</u>
    - 2. Brush
      - (a) <u>Willow</u>
      - (b) <u>Mixed (Sage)</u>
    - 3. Grass
      - (a) <u>Mesic (Meadow)</u>
      - (b) <u>Grass (Sonoran & Montane)</u>
      - (c) <u>Alpine (Xeric &Mesic)</u>
      - (d) <u>Rocky/Grass</u>
- <u>II. Water</u>
- III. Snow
- IV. Shadow

San Juan National Forest
Ground Cover Type Key - Contract

The objective of this key is to classify the total area within the San Juan National Forest into one of 18 cover types by three acre cells.

I. LAND - Cells covered by > 50% land.

Yes - Go to I.A.
No - Go to II.

I. A. FOREST - Cells covered by tree species >30% crown cover. (Trees are further defined as woody vegetation capable of producing a woody stem ≥ 12 feet in height. This includes oak and other tree species that < 12 feet in height due to site limiting conditions.)

Yes - Go to I.A. 1. or 2.
No - Go to I.B.

I. A.1. COMMERCIAL FOREST - >50% of the crown cover is one or more of the following commercial species: ponderosa pine, spruce-fir, Douglas-fir, aspen, or cottonwood.

Yes - Go to I.A. 1. (a) or (b)
No - Go to I.A. 2.

I. A.1. (a) HARDWOOD - >50% of the crown cover is one or more of the following hardwood species: Aspen or Cottonwood.

Yes - Go to I.A. 1. (a) (1) or (2)
No - Go to I.A. 1. (b)

I. A.1. (a) (1) ASPEN/COTTONWOOD - >70% of the crown cover is Aspen or Cottonwood.

Yes - The cover type is Aspen/Cottonwood.
No - Go to I.A. 1. (a) (2).

I. A.1. (a) (2) ASPEN/CONIFER - Aspen crown cover is >50% but not > 70%. The conifer crown cover is < 50% but not < 30%.

Yes - The cover type is Aspen/Conifer.

I. A.1. (b) CONIFER - >50% of the crown cover is one or more of the following conifer species: ponderosa pine, spruce-fir, or Douglas-fir.

Yes - Go to I.A.1. (b) (1), (2), (3), (4) or (5).

I. A.1. (b) (1) PONDEROSA PINE - >70% of the crown cover is ponderosa pine.

Yes - The cover type is ponderosa pine.
No - Go to I.A.1. (b) (2), (3), (4), or (5).

I. A.1. (b) (2) SPRUCE-FIR - >70% of the crown cover is mixed spruce and fir.

Yes - The cover type is spruce-fir.
No - Go to I.A. 1. (b) (3), (4) or (5).

I. A.1. (b) (3) DOUGLAS-FIR - >70% of the crown cover is mixed Douglas-fir and white fir.

Yes - The cover type is Douglas-fir.
No - Go to I. A. 1. (4) or (5).

I. A.1. (b) (4) PONDEROSA PINE/OAK - Ponderosa pine crown cover is >50% but not >70%. The oak crown cover is < 50% but not < 30%.

Yes - The cover type is ponderosa pine/oak.
No - Go to I.A.1. (b) (5).

I. A.1. (b) (5) CONIFER/ASPEN - Conifer crown cover is > 50% but not > 70%. The aspen crown cover is < 50% but not < 30%.

Yes - The cover type is Conifer/Aspen.

I. A.2. NONCOMMERCIAL FOREST - >50% of the crown cover is one or more of the following noncommercial species: pinon pine, juniper, or oak.

Yes - Go to I.A. 2. (a) (b) or (c)

I. A.2. (a) OAK - >70% of the crown cover present is oak.

Yes - The ground cover type is oak.
No - Go to I.A. 2. (b) or (c).

I. A.2. (b) PINON/JUNIPER - >50% of the crown cover present is pinon/juniper.

Yes - The ground cover type is pinon/juniper.
No - Go to I.A.2. (c).

I. A.2. (c) OAK/CONIFER - Oak crown cover is >50%, but not >70%. The conif crown cover is < 50% but not < 30%.

Yes - The ground cover type is oak/conifer.

I. B. NONFOREST - Cells covered by < 30% crown cover of tree species.
Yes - Go to I.B., 1. 2. or 3.

I. B.1. ROCK/BARREN - < 30% vegetative ground cover is present.

Yes - Cover type is Rock/Barren.
No - Go to I.B. 2 or 3.

I. B.2. BRUSH - > 30% of the area is covered by brush species.

Yes - Go to I.B. 2. (a) or (b)
No - Go to I.B. 3.

I. B.2. (a) WILLOW (Brush) - > 30% willow crown cover is present.

Yes - The cover type is Willow.
No - Go to I.B. 2. (b).

I. B.2. (b) MIXED BRUSH (Sage) - > 30% of the area is brush other than oakbrush or willows.

Yes - The cover type is Mixed Brush (Sage).

I. B.3. GRASS - > 30% of the area is grass and herbaceous plants.

Yes - Go to I.B. 3. (a) (b) (c) or (d).

I. B.3. (a) WET or MESIC GRASSLAND - The area is dominated by grasses and other herbaceous plants requiring constant water availability. The elevation range for this cover type is 6,500 feet to 11,000 feet.

Yes - The cover type is Wet or Mesic Grassland.
No - Go to I. B. 3. (b), (c) or (d).

I. B.3. (b) GRASSLAND (Sonoran and Mountain) - The area is dominated by grasses and other herbaceous plants. The elevation range is 6,500 feet to 11,000 feet.

Yes - The cover type is Grassland.
No - Go to I.B.3. (c) or (d).

I. B.3. (c) ALPINE (Xeric and Mesic) - The area is above timberline and dominated by grass and other herbaceous plants. The elevation range of this cover type is > 11,000 feet.

Yes - The cover type is ALPINE (Xeric and Mesic).
No - Go to I.B. 3. (d).

I. B.3. (d) ROCKY/GRASSLAND - The area is dominated by grasses and other herbaceous species. Rock and barren soil cover >30% but <50% of the area. The elevation range of the area is >6,500.

Yes - The cover type is Rocky/Grassland.

II. WATER - Cells covered by >50% water.

Yes - Ground cover type is water.

III. SNOW - This cover class division is included because areas will seasonally be covered with snow. Landsat will record this information, if present. Snow is not a valid ground cover type.

IV. SHADOW - This cover class division is included because steep topography on the Forest produces shaded cells regardless of sun angle. Landsat will record this information, if present. Shadow is not a valid ground cover type.

San Juan National Forest
Ground Cover Type Key - Data Base
(Cover types are underlined.)

I.	Lands
I.A.	Forest (> 10% stocked)
I.A.1.	Forest (> 30%)
I.A.1.a.	Commercial Forest
I.A.1.a.(1)	Hardwood
I.A.1.a.(1)(a)	Cottonwood (> 30%)
I.A.1.a.(1)(b)	Aspen (> 30%)
I.A.1.a.(2)	Conifer
I.A.1.a.(2)(a)	Ponderosa Pine (> 30%)
I.A.1.a.(2)(b)	Spruce-fir (> 30%)
I.A.1.a.(2)(c)	Douglas-fir (> 30%)
I.A.1.b.	Non-Commercial
I.A.1.b.(1)	Oak (> 30%)
I.A.1.b.(2)	Pinon Juniper (> 30%)
I.A.2.	Forest (10-30%)
I.A.2.a.	Commercial Forest
I.A.2.a.(1)	Hardwood
I.A.2.a.(1)(a)	Cottonwood (10-30%)
I.A.2.a.(1)(b)	Aspen (10-30%)
I.A.2.a.(2)	Conifer
I.A.2.a.(2)(a)	Ponderosa Pine (10-30%)
I.A.2.a.(2)(b)	Spruce-fir (10-30%)
I.A.2.a.(2)(c)	Douglas-fir (10-30%)
I.A.2.b.	Non-Commercial
I.A.2.b.(1)	Oak (10-30%)
I.A.2.b.(2)	Pinon Juniper (10-30%)
I.B.	Non-Forest (less than 10% stock)
I.B.1.	Rock/Barren
I.B.2.	Brush
I.B.2.a.	Willow
I.B.2.b.	Mixed Brush
I.B.2.c.	Sage
I.B.3.	Grass
I.B.3.a.	Meadow
I.B.3.b.	Sonoran
I.B.3.c.	Montane
I.B.3.d.	Alpine Xeric
I.B.3.e.	Alpine Mesic
II.	Water
III.	Snow
IV.	Shadow

SAN JUAN NATIONAL FOREST
Ground Cover Type Key - Data Base
(Cover types are underlined)

- I. Land
  - A. Forest (>10% stocked)
    - 1. Forest (>50%)
      - a. Commercial Forest
        - (1) Hardwood
          - (a) Cottonwood
          - (b) Aspen
        - (2) Conifer
          - (a) Ponderosa Pine
          - (b) Spruce-Fir
          - (c) Douglas-Fir
      - b. Non Commercial Forest
        - (1) Oak
        - (2) Pinon/Juniper
    - 2. Forest (10%-50%)
      - a. Commercial Forest
        - (1) Hardwood
          - (a) Cottonwood
          - (b) Aspen
        - (2) Conifer
          - (a) Ponderosa Pine
          - (b) Spruce-fir
          - (c) Douglas-fir
      - b. Non Commercial Forest
        - (1) Oak
        - (2) Pinon/Juniper
  - B. Non Forest (Less than 10% stocked)
    - 1. Rock/Barren
    - 2. Brush
      - a. Willow
      - b. Mixed
      - c. Sage
    - 3. Grass
      - a. Meadow
      - b. Sonoran
      - c. Montain
      - d. Alpine Xeric
      - e. Alpine Mesic
- II. Water
- III. Snow
- IV. Shadow

San Juan National Forest
Ground Cover Type Key - Data Base

The objective of this key is to classify the total area within the San Juan National Forest into one of 25 cover types by three acre cells.

I. LAND - Cell covered by >50% land.

Yes - Go to I.A.
No - Go to II.

I. A. FOREST (>10% stocked) - Cells covered by tree species >10% crown cover. (Trees are further defined as woody vegetation capable of producing a woody stem ≥12 feet in height. This includes oak and other tree species that are < 12 feet in height due to site limiting conditions.)

Yes - Go to I.A.1. or 2.
No. - Go to I.B.

I. A.1. FOREST (>30%) - Cells covered by tree species >50% crown cover.

Yes - Go to I.A.1. a. or b.
No - Go to I.A.2.

I.A.1.a COMMERCIAL FOREST - >50% of the crown cover is one or more of the following commercial species: ponderosa pine, spruce-fir, Douglas-fir, aspen, or cottonwood.

Yes - Go to I.A.1.a.(1) or (2).
No - Go to I.A.1.b.

I. A.1.a.(1) HARDWOOD - >50% of the crown cover is one or more of the following hardwood species: Aspen or Cottonwood.

Yes - Go to I.A.1.a.(1) (a) or (b).
No - Go to I.A.1.a.(2).

I. A.1.a.(1)(a) COTTONWOOD - >50% of the crown cover is Cottonwood.

Yes - <u>The cover type is Cottonwood (>30%)</u>.
No - Go to I.A.1.a.(1).(b).

I.A.1.a.(1)(b) ASPEN - >50% of the crown cover is aspen.

Yes - <u>The cover type is aspen (>30%)</u>.

I.A.1.a.(2) CONIFER - >50% of the crown cover is one or more of the following conifer species: ponderosa pine, spruce-fir, or Douglas-fir.

Yes - Go to I.A.1.a.(2) (a), (b), or (c).

I.A.1.a.(2)(a) PONDEROSA PINE - >50% of the crown cover is Ponderosa Pine.

Yes - The cover type is Ponderosa Pine (>30%).
No - Go to I.A.1.a.(2) (b) or (c).

I.A.1.a.(2)(b) SPRUCE-FIR - >50% of the crown cover is spruce-fir.

Yes - The cover type is spruce-fir (>30%).
No - Go to I.A.1.a.(2)(c).

I.A.1.a.(2)(c) DOUGLAS FIR - >50% of the crown cover is mixed Douglas fir and white fir.

Yes - The cover type is Douglas fir (>30%).

I.A.1.b. NON-COMMERCIAL - >50% of the crown cover is one or more of the following non-commercial species: pinon pine, juniper, or oak.

Yes - Go to I.A.1.b. (1) or (2).

I.A.1.b.(1) OAK - >50% of the crown cover is oak.

Yes - The cover type is oak (>30%).
No - Go to I.A.1.b.(2).

I.A.1.b.(2) PINON-JUNIPER - >50% of the crown cover is pinon/juniper.

Yes - The cover type is pinon-juniper (>30%).

I.A.2. FOREST (10-30%) - Cells covered by tree species. 10-30% crown cover.

Yes - Go to I.A.2. a. or b.

I.A.2.a. COMMERCIAL FOREST ->50% of the crown cover is one or more of the following commercial species: ponderosa pine, spruce-fir, Douglas fir, aspen, or cottonwood.

Yes - Go to I.A.2.a. (1) or (2).
No - Go to I.A.2.b.

I.A.2.a.(1) HARDWOOD ->50% of the crown cover is one or more of the following hardwood species: Aspen or cottonwood.

Yes - Go to I.A.2.a.(1) (a) or (b).
No - Go to I.A.2.a.(2).

I.A.2.a.(1)(a) COTTONWOOD - >50% of the crown cover is cottonwood.

Yes - The cover type is cottonwood (10-30%).
No - Go to I.A.2.a.(1)(b).

I.A.2.a.(1)(b) ASPEN - $>$50% of the crown cover is aspen.

Yes - The cover type is aspen (10-30%).

I.A.2.a.(2) CONIFER - $>$50% of the crown cover is one or more of the following conifer species: ponderosa pine, spruce-fir, or Douglas fir.

Yes - Go to I.A.2.a.(2) (a), (b), or (c).

I.A.2.a.(2)(a) PONDEROSA PINE - $>$50% of the crown cover is ponderosa pine.

Yes - The cover type is ponderosa pine (10-30%).
No - Go to I.A.2.a.(2) (b) or (c).

I.A.2.a.(2)(b) SPRUCE-FIR - $>$50% of the crown cover is spruce-fir.

Yes - The cover type is spruce-fir (10-30%).
No - Go to I.A.2.a.(2)(c).

I.A.2.a.(2)(c) DOUGLAS FIR - $>$50% of the crown cover is mixed Douglas fir and white fir.

Yes - The cover type is Douglas fir (10-30%).

I.A.2.b. NON-COMMERCIAL - $>$50% of the crown cover is one or more of the following non-commercial species: pinon pine, juniper, or oak.

Yes - Go to I.A.2.b. (1) or (2).

I.A.2.b.(1) OAK - $>$50% crown cover is oak.

Yes - The cover type is oak (10-30%).
No - Go to I.A.2.b.(2).

I.A.2.b.(2) PINON-JUNIPER - $>$50% of the crown cover is pinon juniper.

Yes - The cover type is pinon-juniper (10-30%).

I.B. NON-FOREST (less than 10% stocking) - Cells covered by $<$10% crown cover of tree species.

Yes - Go to I.B., 1., 2., or 3.

I.B.1. ROCK/BARREN - $<$30% vegetative ground cover is present.

Yes - Cover type is rock/barren.
No - Go to I.B. 2 or 3.

I.B.2. BRUSH - $>$30% of the area is covered by brush species.

Yes - Go to I.B.2. a, b, or c.
No - Go to I.B.3.

I.B.2.a. WILLOW (brush) - >30% willow crown cover is present.

Yes - The cover type is willow.
No - Go to I.B.2. b or c.

I.B.2.b. MIXED BRUSH - >30% of the area is brush other than oakbrush, willow, or sage.

Yes - The cover type is mixed brush.
No - Go to I.B.2.c.

I.B.2.c. SAGE BRUSH - > 30% sage brush crown cover is present.

Yes - The cover type is sage brush.

I.B.3. GRASS - >30% of the area is grass and herbaceous plants.

Yes - Go to I.B.3. a, b, c, d, or e.

I.B.3.a. MEADOWS (wet) - The area is dominated by grasses and other herbaceous plants requiring constant water availability. The elevation range for this cover type is > 5,500 feet.

Yes - The cover type is meadow.
No - Go to I.B.3. b, c, d, or e.

I.B.3.b. SONORAN GRASSLAND - The area is dominated by grasses and other herbaceous plants. The elevation range is 5,500 to 7,000 feet.

Yes - The cover type is Sonoran grassland.
No - Go to I.B.3. c, d, or e.

I.B.3.c. MONTANE GRASSLAND - The area is dominated by grasses and other herbaceous plants. The elevation range is 6,900 to 9,000 feet.

Yes - The cover type is Montane grassland.
No - Go to I.B.3. d or e.

I.B.3.d. ALPINE XERIC - The area is above timberline and dominated by dry site grasses and other herbaceous plants. The elevation range of this cover type is > 11,000 feet.

Yes - The cover type is Alpine Xeric.
No - Go to I.B.3.e.

I.B.3.e. ALPINE MESIC - The area is above timberline and dominated by wet or moist site grasses and other herbaceous plants. The elevation range of this cover type is > 11,000 feet.

Yes - The cover type is Alpine Mesic.

II. WATER - Cells covered by > 50% water.

Yes - <u>Ground cover type is water</u>.

III. SNOW - This cover class division is included because areas will seasonally be covered with snow. Landsat will record this information, if present. Snow is not a valid ground cover type.

IV. SHADOW - This cover class division is included because steep topography on the Forest produces shaded cells regardless of sun angle. Landsat will record this information, if present. Shadow is not a valid ground cover type.

**INTERMOUNTAIN FOREST
AND RANGE EXP. STATION**
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